Sense-Through-Wall Human Detection Using UWB Radar With Sparse SVD

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Abstract

In this paper, a method for through-wall human detection based on the singular values decomposition of the measurement matrices is presented. After demonstrating the sparsity of the matrices using CLEAN algorithm, an SVD algorithm based on Lanczos process is applied to compute their singular values. We also analyze the singular values of matrices constructed by difference square techniques for different types of walls and compare our algorithm with a 2-D imaging approach proposed by researchers in Time Domain Company. Detection results show that our method performs well in gypsum wall, brick wall, and wooden door.

Keywords: Through-wall Detection, UWB, Singular Value Decomposition, Lanczos Process

1. Introduction

UWB radars are used nowadays for different applications such as subsurface sensing, classification of aircrafts, collision avoidance, etc. In all of these applications the ultra-high resolution of UWB radars is essentially used [1]. UWB radar emissions are at a relatively low frequency-typically between 100 MHz and 3 GHz. Additionally, the fractional bandwidth of the signal is very large (greater than 0.25). In this definition, bandwidth means the difference between the highest and lowest frequencies of interest and contains about 95% of the signal power [2][3]. Such radar sensor has exceptional

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range resolution that also has an ability to penetrate many common materials (e.g., walls). Law enforcement personnel have used UWB ground penetrating radars (GPRs) for at least a decade. In 1995, James D. Taylor's [3] Introduction to Ultra-Wideband Radar Systems introduced engineers to the theory behind a promising new concept for remote sensing. Since then, the field has undergone enormous growth with new applications realized and more applications conceptualized at a remarkable pace [2], such as through-wall detection. In [4], Immoreev gave an overview on new practical applications of UWB radars. In [5], through-wall UWB radar operating within FCC's mask was studied for heart beat and breathing rate. In [1][6][7], UWB radar for detection and positioning of human beings in a complex environment was studied. Recently, UWB radars were used in sense-through-foliage target detection [8][9][10][11][12].

Through-wall detection has a variety of application, not only in military industry but for security and rescuing as well. Many of these applications prefer to choose UWB radar due to its good penetration through non-metallic building materials and high resolution as a result of small pulse duration.

Detection of human beings with radars is based on movement detection [13] [14]. In [15], an algorithm designed for respiration motion detection was proposed. It separates the nonstationary clutter from the respiratory-motion response, which leads a significantly higher detection rate in low signal-to-noise-and-clutter ratio (SNCR) conditions than for the detection algorithm presented in [16]. Three different detection techniques is discussed in [17] for different types of walls. Both the Doppler based method with Discete Fourier Transform(DFT) and the clutter reduction method using singular value decomposition work for gypsum wall, brick wall and wooden door, but fail in case of a thick concrete wall. And only for gypsum wall, the second singular value, computed by the new approach based on STFT and SVD, changes relatively in presence of target. The method presented in [18] is based on the detection of body movement and using Fast Fourier Transform and S transform. It has high accuracy and can be implemented simply in complex environment with strong clutter.

The remaining of this paper is organized as follows. Section 2 describes the specifications of the UWB radar used in this experiment and the configuration of the environment where the measurements are taken. The sparsity of the measurement matrix is demonstrated in Section 3 using a variant of CLEAN Algorithm. Section 4 introduces the sparse SVD algorithm used for Target detection and its advantages. Finally, experiment results are shown in Section 5 and the conclusions are drawn in Section 6.

2. Experiment Setup

The experiment is based on the data collected with an Ultra-WideBand (UWB) radar 'PulseON 220' manufactured by Time Domain Corporation. The radar has a center frequency of 4.3 GHz with 10-dB bandwidth at 2.3 GHz and provides a resolution of 6.5 cm as its pulse duration is 430 pS. Ported with two omni-directional antenna, the radar works in monostatic mode as shown in figure 1.

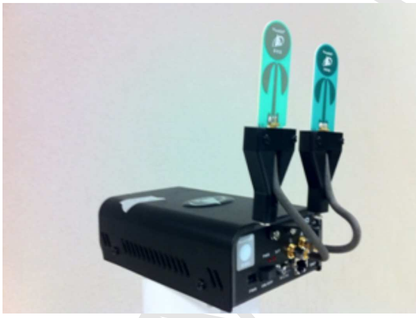

Figure 1: P220 in Monostatic mode

The radar was configured using GUI PulsON 220 MSR 1.1 application software provided with the radios. The pulse repetition frequency was set to the highest supported rate of the radar, 9.6 MHz, at which the maximum unambiguous range is approximately 50 ft. By setting the Window Size and the Step Size to 10 ft and 1 bin respectively, there were about 6400 samples per scan. The scan rate of the radar was calculated to be 1.47 scans/sec after setting its Hardware Integration to 512 and software integration to 2. So, 100 scans were captured in each measurements set for a total time duration of 68 sec.

The measurements were taken on different sides of a 1-ft thick Gypsum partition wall at UTA (NH room 202 & 203). The UWB radar was located on one side of the wall and the height of its antennas from ground was 3.3 ft. Person was standing at a distance of 6.5 ft from the radar on the other side of the wall. A set of measurements taken with person and another set taken without target are considered in this experiment.

Figure 2: UWB radar (Right), Human target (Left)

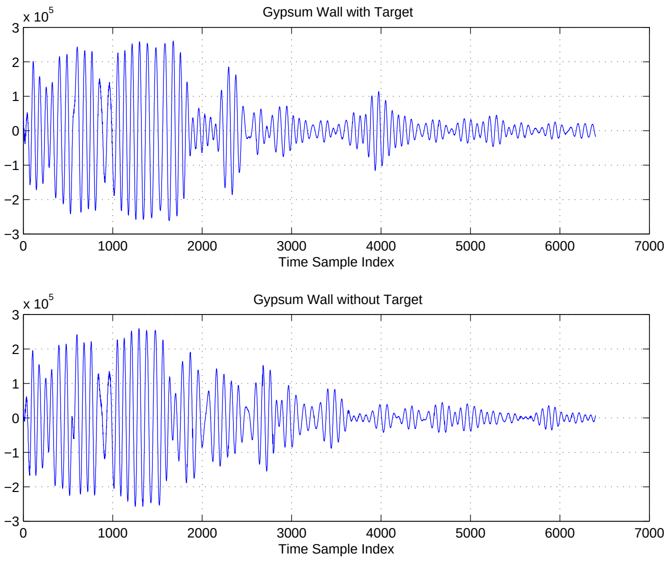

Figure 3: Single Scan For Gypsum Wall

3. Sparsity Analysis

We applied a variant of the CLEAN algorithm introduced in [19]to extract the channel Impulse response, which is then used to demonstrate the Sparsity of the Measurement Matrix.

The CLEAN algorithm, first introduced in [20] is a commonly used deconvolution technique in the radio astronomy and microwave communities. It has been applied in communication channel characterization problems in [21] and [22] and modified to process impulsive UWB measurements by [23] and [24]. In [19] a variant of the CLEAN algorithm is proposed to extract the channel Impulse response by deconvolving the effects of the measurement system from the received echoes. The main procedure of the algorithm is searching the received echoes iteratively with the transmitted pulses to find the maximum correlation [25], as shown in the following steps.

Step 1: Calculate the autocorrelation of the transmit pulses $rss(t)$ and the cross-correlation of the transmit pulses with the received echoes $rsy(t)$.

Step 2: Find the largest correlation peak in $rsy(t)$, record the normalized amplitudes α_k and relative time delay τ_k of the correlation peak.

Step 3: Subtract $rss(t)$ scaled by α_k from $rsy(t)$ at the time delay τ_k.

Step 4: If a stopping criterion (e.g., a minimum threshold on the peak correlation) is not met, go to step 2. Otherwise stop.

The channel impulse response $h = [h_1, h_2, \ldots, h_n]$ extracted by the variant of the CLEAN algorithm based on one experiment is plotted in figure 4 and it shows that h has very few nonzero taps. If no noise, the received echo could be represented as

$$y(i) = h * \psi(i) = \sum_{j=1}^{n} h_i \psi(i-j) = \Psi h$$

where $\psi(i)$ represents the transmit pulse and $\Psi = [\psi_1, \psi_2, \ldots, \psi_n]$ represents the transform domain functions. Since most values in h are zeroes under the transform basis , so the measurement matrix constructed by the received echoes y is sparse. Since the UWB radar echoes are sparse, we apply sparse singular value decomposition (SVD) to target detection.

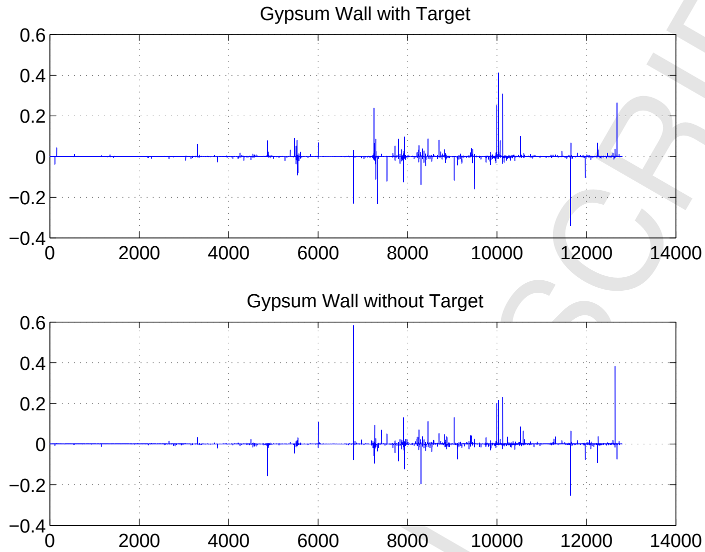

Figure 4: Channel Impulse Response h

4. Target Detection

In the experiments, the target is identified according the selected singular value of the measurements matrix which can be computed by a sparse SVD algorithm based on Lanczos Bidiagonalization [26].

Based on the relationship between the singular value decomposition of a matrix A and the schur decomposition of some related symmetric matrices, the singular values and vectors of A can be obtained by computing the eigenvalue and corresponding eigenvectors of those symmetric matrices. For example, the commonly used SVD algorithm, proposed by Golub and Kahan [26], obtains the singular vectors by solving the symmetric eigenvalue problem of $A^T A$. It first reduces A to a bidiagonal matrix B by Householder transformation, and then implicitly applies the QR algorithms on the symmetric tridiagonal matrix $B^T B$. Since $B^T B$ is orthogonally equivalent to $A^T A$, they have the same eigenvalues which equals to the square of the singular values of A. However, this algorithm is not preferable if A is large and sparse because the Householder bidiagonalization successively updates A and destroys its sparsity.

The sparse SVD algorithm used here applies the Lanczos process on $A^T A$

to get a tridiagonal matrix T_k and then obtain the selected singular values by computing the eigenvalues of T_k. Different from the Householder transformation, the Lanczos process [27], as shown in Algorithm 1, computes the diagonal and subdiagonal elements of the tridiagonal matrix directly, and can be implemented by only involving A in procedures of Matrix-vector products. Moreover, this process extract information about the largest and smallest eigenvalues values of the tridiagonal matrix early during its iteration steps, and make it possible to obtain part of the extreme eigenvalues before full Tridiagonalization. Therefore, the sparse SVD algorithm is very useful when only a few of the largest singular values are desired.

Algorithm 1 Lanczos Process on a rectangular $m \times n$ matrix to generate the diagonal element α_k and the subdiagonal element β_k of a tridiagonal matrix T_k

Choose a starting vector $p_0 \in R^m$, and let $\beta_1 = \| p_0 \|_2$, $u_1 = p_0/\beta_1$ and $v_0 \equiv 0$
for j = 1, 2, ..., k **do**
  $r_j = A^T u_j - \beta_j v_{j-1}$
  $\alpha_j = \| r_j \|_2$
  $v_j = r_j/\alpha_j$
  $p_j = Av_j - \alpha_j u_j$
  $\beta_{j+1} = \| p_j \|_2$
  $u_{j+1} = p_j/\beta_{j+1}$
end for

To apply sparse SVD algorithm to target detection, we have two ways to construct matrix A. To detect the target, this experiment compares the 20 largest singular values of the matrices constructed using the two sets of measurements. One comparison uses the matrix A constructed by arranging each scan in a column. The other comparisons require to construct the matrix A_{diff} by difference square techniques. Suppose the measurements set contains M scans, and each scan has N samples. The simple matrix A and the difference square matrix A_{diff} are constructed as follows.

$$A = \begin{bmatrix} Scan_1 & Scan_2 & \dots & Scan_M \\ s_{11} & s_{12} & \dots & s_{1M} \\ s_{21} & s_{22} & \dots & s_{2M} \\ & & \ddots & \\ s_{N1} & s_{N2} & \dots & s_{NM} \end{bmatrix}$$

$$A_{diff} = \begin{bmatrix} (Scan_1 - Scan_2)^2 & (Scan_2 - Scan_3)^2 & \dots & (Scan_{(M-1)} - Scan_M)^2 \\ (s_{11} - s_{12})^2 & (s_{12} - s_{13})^2 & \dots & (s_{1(M-1)} - s_{1M})^2 \\ (s_{21} - s_{22})^2 & (s_{22} - s_{23})^2 & \dots & (s_{2(M-1)} - s_{2M})^2 \\ & & \ddots & \\ (s_{N1} - s_{N2})^2 & (s_{N2} - s_{N3})^2 & \dots & (s_{N(M-1)} - s_{NM})^2 \end{bmatrix}$$

5. Experiment Result

Figure 5 shows the 20 largest singular values of A for gypsum wall. The comparison from the second value specified as start shows that there are obvious increases of the largest singular values of measurements with target.

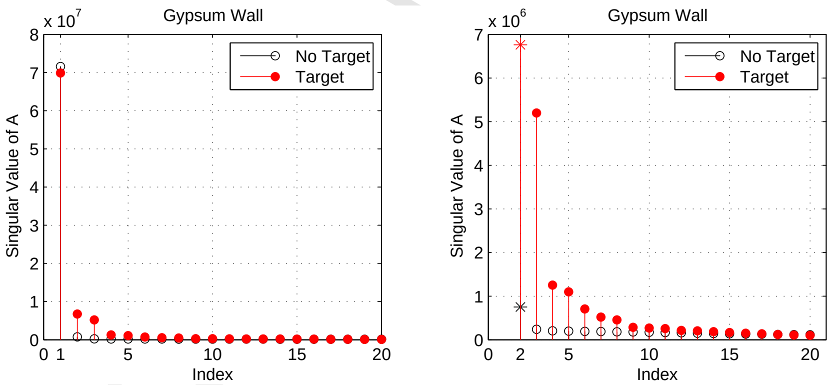

Figure 5: The Singular Value of A for Gypsum Wall

The singular values of A_{diff} for different kinds of walls are plotted in figure 6. It shows that all the 5 largest singular values specified as starts of measurement with target increase for Gypsum wall, Brick wall and Wooden door. If the singular values are normalized by dividing each value with the first singular value, there will be decreases from the fourth normalized value to the tenth normalized value for any kind of wall. Based on the figures, we can make the following observations:

1) Our method performs well in gypsum wall, brick wall, and wooden door.
2) It is hard to perform sense-through-wall human detection when the wall is concrete wall.

We also compare our algorithm with an existing algorithm proposed by researchers in Time Domain Company [28], a 2-D imaging approach, in which a 2-D image could be created via adding voltages with the appropriate time offset. The representative images created by single scans for Gypsum Wall is shown in figure 7. In the left image created by a single scan with target, the yellow bars located near 6 ft represent the target, but 20 percent of the images are same as the middle one by which the target cannot be detected. Moreover, the middle image is similar to the right one created by a single scan without target. Therefore, although the 2-D imaging approach has the ability to identify the target quickly by only one single scan, the detection result is not reliable and is affected by the clutter.

6. Conclusion

The sparse SVD algorithm makes it possible to detect target and the measurement matrix constructed by difference square techniques generates more obvious detection result. Detection results show that our method performs well in gypsum wall, brick wall, and wooden door, however, the results is not reliable enough when it is applied to concrete wall. Compared with other human detection methods, only perform SVD with the measurements can not provide the extract position of the target.

Acknowledgement

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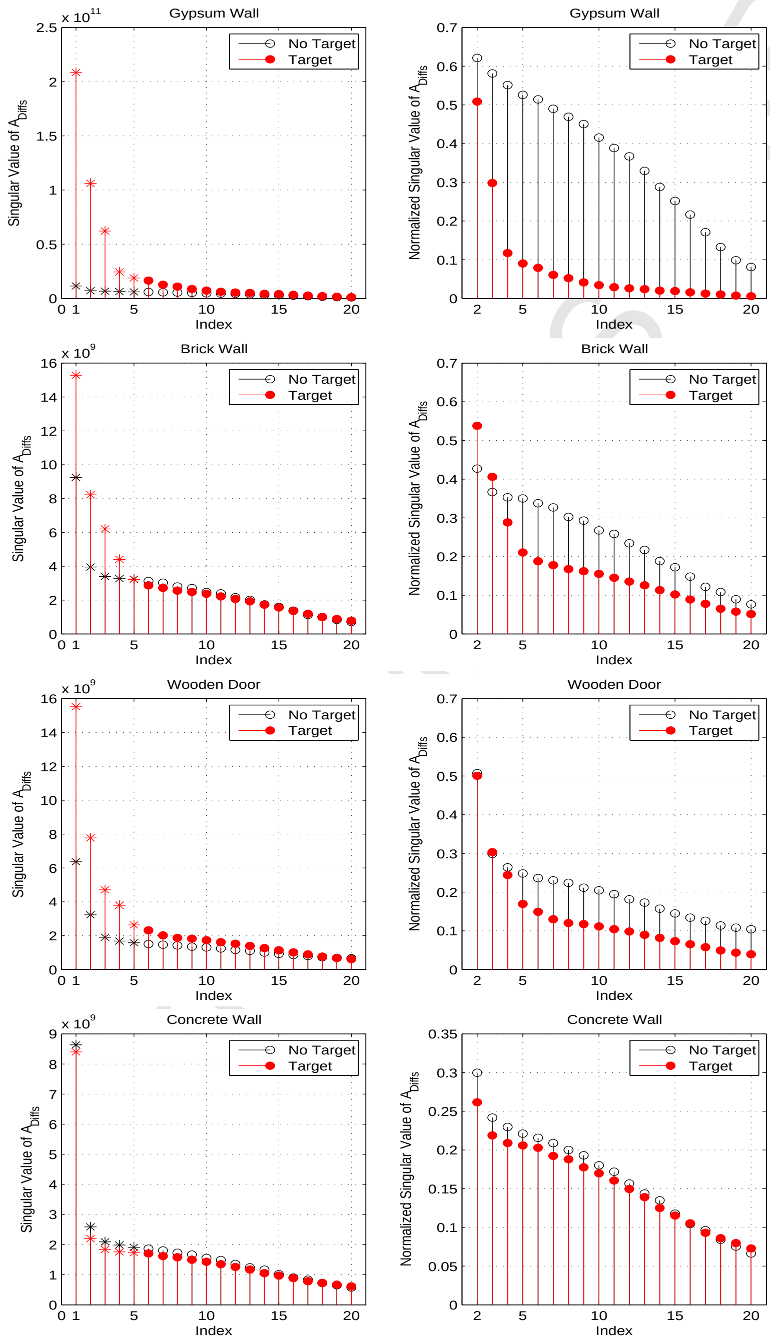

Figure 6: The Singular Value of A_{diff} for different kinds of walls

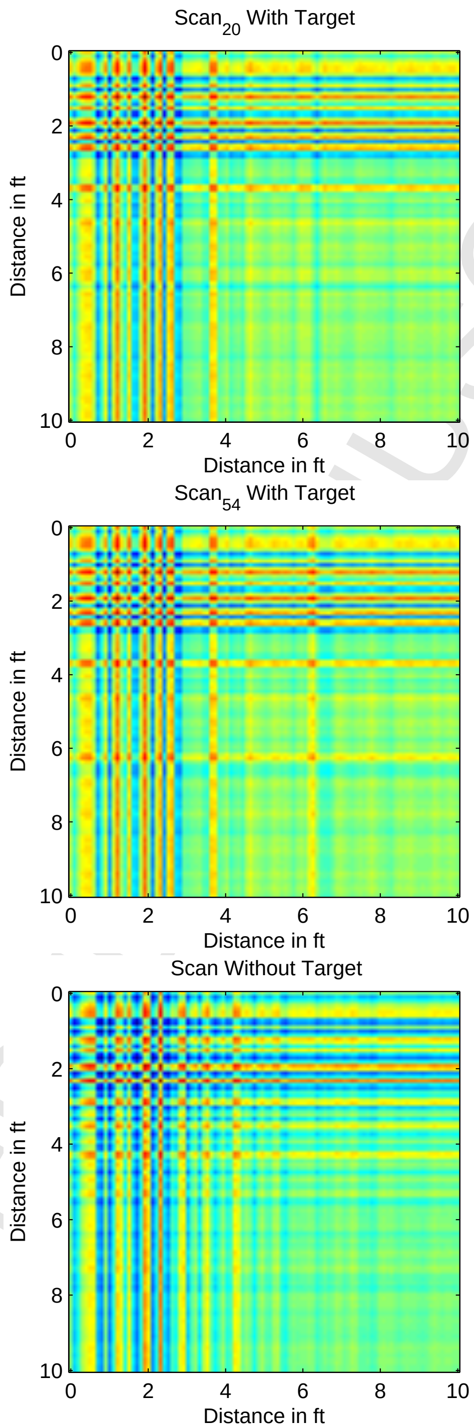

Figure 7: 2-D Images Created with Single Scans for Gypsum Wall

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